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Authors
Sadek, Bassel A
Martin, Elliot W
Shaheen, Susan A

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Bassel A. Sadek

Elliot Martin

Susan A. Shaheen

Truck Parking Forecasting using Fourier Transformations

Bassel A. Sadek[a*], Elliot W. Martin[b], Susan A. Shaheen[c]

[a]*PhD Candidate, Department of Civil and Environmental Engineering, University of California, Berkeley, 416F McLaughlin Hall, Berkeley, CA 94720-1720, United States, bas11@berkeley.edu*
[b]*Research and Development Engineer, University of California, Berkeley, Transportation Sustainability Research Center, 1301 S. 46th Street, Bldg. 190, Richmond, CA 94804, United States, elliot@berkeley.edu*
[c]*Professor In-Residence of Civil and Environmental Engineering and Co-Director of Transportation Sustainability Research Center, University of California, Berkeley, 408 McLaughlin Hall, Berkeley, CA 94720, United States, shaheen@berkeley.edu*

Abstract - Truck-based transportation is the predominant mode used to transport goods and raw materials within the United States. While trucks play a major role in local commerce, a significant portion of truck activity is also long-haul in nature. Long-haul truck drivers are continuously faced with the problem of not being able to secure a safe parking spot since many rest areas become fully occupied, and information about parking and availability is limited. Truck drivers faced with full parking lots/facilities either continue driving until a safe parking spot is located or park illegally. Both scenarios pose a hazard to the truck driver, as well as the surrounding road users. Disseminating forecasts of parking availability to truck drivers may help mitigate this hazard, since many truck drivers plan their parking in advance of arrival. Building on one year of nearly continuous truck parking data collection, this paper proposes and demonstrates a method for developing a dynamic forecasting model that can predict truck parking occupancy for any specified time within the present day, using only truck parking occupancy data from a trucking logistics facility in the northern San Joaquin Valley during 2016. Different versions of the dynamic model were studied and verified against successive weekdays with performance measured using the Root Mean Square Error (RMSE). Results indicated that for a particular day, the maximum error can range between 13 to 40 trucks, about 5% of the absolute maximum capacity of the facility.

Keywords: Truck Parking; Time Series; Fourier; Forecasting

1. Introduction

The United States (U.S.) is one of the largest trading nations in the world (Inman 2013). In 2012, the nation's freight transportation system moved nearly 11.7 billion tons of raw materials and finished goods. Of those 11.7

* Corresponding Author.
E-mail address: bas11@berkeley.edu

billion tons, more than 70% were transported by commercial trucks (Bureau of Transportation Statistics 2013). By a number of different measures, trucking is the dominant mode of freight transport in the U.S. It is critical to ensure that all facilities, complementing road freight transport, are adequately provided.

Truck drivers transporting goods and raw materials for long distances need to stop and rest. Federal Hours of Service (HOS) regulations require truck drivers to park after 11 hours of driving and no more than 14 hours of work during the day (Federal Motor Carrier Administration 2015). At the same time, truckers often encounter extreme difficulties in finding available parking. This problem is in part due to a lack of capacity in high traffic areas, as well as limited information on where parking is and whether it is available.

Lack of truck parking availability can cause serious hazards. If truck drivers arrive at a cluster of parking stations that are completely occupied, particularly when nearing their HOS limit, they must choose to either continue driving or park illegally. Truck drivers who decide to continue driving might risk violating the HOS regulations. Furthermore, they might become fatigued and tired while searching for an empty parking spot and thus place themselves and the public at risk of being involved in a crash. Similarly, if truck drivers decide to park illegally or in remote locations, they are faced with the traffic hazards of road-side parking, as well as the criminal hazards of parking in locations remote from the company of others. The criminal hazards associated with limited parking were tragically central to the case of Jason Rivenburg, a truck driver that was murdered while parking at a vacant gas station in South Carolina (Federal Highway Administration 2015). In light of these issues, several laws were enacted and coalitions were formed to help improve the current truck parking situation. Jason's Law gave rise to several key objectives and policies that aimed to improve the infrastructure surrounding truck stops and rest areas. Moreover, the National Coalition on Truck Parking, which consists of trucking organizations, state Departments of Transportation, and others, was formed amid calls for devising immediate near-term and long-term solutions to address the difficulties faced by truck drivers when searching for a safe and secure parking spot.

While increasing the capacity of parking locations or constructing new facilities along interstate highways is a straight-forward solution, it is financially expensive, politically challenging, and time consuming. Disseminating truck parking information is another solution that can help address parking issues without additional construction. Truck parking information is generally broken into two types: 1) static information, which is information that changes infrequently, pertaining to the locations, capacities, and attributes of truck parking facilities and 2) dynamic information, which is time-dependent information about the availability of truck parking at a particular location. Truck parking availability information is the most common type of dynamic information for truck parking, and it is derived from the deployment of sensing technologies at truck stops.

There are now quite a few websites and smartphone applications (e.g., Allstays, Trucker Path, Truck Specialized Parking Services, Park My Truck, American Truck Parking, etc.) that provide truck drivers with information regarding the locations of truck stops and rest areas across the U.S.. Some applications provide availability data, and there are a number of federally sponsored projects in states including: Michigan, Minnesota, Tennessee, Maryland, Virginia, California, Florida, among others, which have developed and deployed sensing technologies to experiment with truck parking sensing and information dissemination. These applications have focused on providing current information on truck parking availability for a location near the time of inquiry. This type of information is important and can be useful to the truck driver, but information about anticipated truck parking availability could also be useful. For example, truck parking forecasts can provide truck drivers with information on the expected parking availability at the hours in which they are expected to get there. Providing truck drivers with forecasts of the truck parking occupancy at different truck stops and rest areas could allow them to make informed decisions regarding where and when they should park and rest. At the same time, providing accurate truck parking forecasts requires reliable detection of parking availability in the present. Given the experimental nature of truck parking sensing, long-running accurate information about truck parking availability is required to build such models.

There are two key characteristics inherent to truck parking that are favorable to producing more accurate and reliable forecasts. First, any parking station, truck stop, or rest area has an upper bound on capacity that cannot be exceeded. Even if this capacity is above the “nameplate capacity” of a facility, there is always an “effective capacity” that is simply a function of the physical space in which a facility cannot reasonably or safely accept additional trucks. The presence of this effective capacity simplifies the forecasting problem, since the forecasts can be upper bounded by this value and naturally lower bounded by zero. Second, since most truck drivers behave in a similar manner with respect to the approximate time at which they leave a parking location and the approximate time at which they arrive at a parking location, most truck parking locations are usually subject to some cyclical behavior that repeats itself every day. In other words, there is a common diurnal pattern that exists with respect to truck parking activity. Given these patterns and bounds, we developed a forecasting model that can predict truck parking occupancy at a particular location using historical and real-time truck parking occupancy data collected over a period of one year. This study demonstrates that in practice truck parking forecasting can be executed with rather good accuracy simply through the use of historical activity data collected at the parking facility.

To explore an application of truck parking forecasting, this paper proceeds with a literature review of previous work in truck parking and forecasting. Then, we discuss the data and forecasting methodology. Next, we describe the results of the model's forecasting accuracy. Finally, we provide a summary of the paper with concluding remarks and recommendations.

2. Literature Review

Our summary of the literature includes three main topics relevant to this study including: 1) research in truck parking, 2) previous work in parking forecasting, and 3) selected Fourier modeling applications.

2.1. Truck Parking Research

Extensive research has been conducted on truck parking to better understand the challenges faced by long-haul truck drivers as they transport goods. Garber et al. 2002 estimated and analyzed the supply and demand of truck parking spaces along I-81 in Virginia. The authors reported that the corridor had a deficiency of around 309 truck parking spaces in 2002, and this number was anticipated to increase to 1,463 spaces by 2020, if no new parking spaces were provided (Garber et al. 2002). The supply and demand of truck parking spaces were also analyzed along the three major interstate highways in Washington: I-5, I-90, and I-82 (Parametrix 2005). The study reported that truck parking along I-5, I-90, and I-82 are 37%, 21%, and 7% over capacity on average, respectively (Parametrix 2005). Martin and Shaheen 2013 further assessed truck parking availability along I-5 in California by analyzing results from a survey conducted with truck drivers. Fifty-five percent of the respondents reported that they had come across parking facilities too full to park in during their current trip, while 78% reported that they had experienced similar situations during previous trips on I-5 (Martin and Shaheen 2013). Anderson et al. 2018 conducted a truck driver survey on the experiences of truck drivers related to safe and adequate parking along a primary freight corridor in Oregon. The survey was focused on drivers and freight activity along the Pacific Northwest to better understand truck parking along the study corridor. The authors used the survey data to estimate a binary logit model to evaluate how different factors impact the likelihood of finding safe and adequate parking along the corridor. The study results showed that drivers of less than full truck load shipments, weekend shipments, and older drivers have significantly fewer challenges finding safe and adequate parking. Haque et. al 2017 used truck parking Global Positioning System data to develop econometric models that predict truck parking usage at rest areas to improve truck parking management and ensure proper parking space use. The models were also used to understand the factors that affect truck parking use. Results showed that several factors, such as truck volume on adjacent roadways and the number of lanes positively contribute to truck parking usage, whereas factors such as on-ramp and off-ramp violation decrease truck parking use. Furthermore, the Federal Highway Administration surveyed 8,000 truck drivers, and more than 75% indicated that they regularly have trouble finding parking at night (Boris and Johnson 2015). These studies show that it is common for long-haul truck drivers to arrive at a parking facility and find it at full capacity--a problem long reported by truck drivers themselves. In such cases, truck drivers can either continue driving in search of parking or decide to park illegally (Martin and Shaheen 2013). Because truck stops and public rest areas along interstate highways are often clustered, a truck driver--approaching the driving limit set by the HOS regulation--can be faced with no other choice but to park illegally when arriving at a full truck stop (Boris and Johnson 2015). Illegal parking has several adverse societal impacts including, but not limited to: 1) reduced vehicle speeds, 2) loss of revenue for legal parking operators, and 3) a significant increase in the number of accidents (Nourinejad and Roorda 2016). As noted earlier, illegal truck parking in remote locations is also associated with criminal hazards (Federal Highway Administration 2015). These studies motivate calls for truck parking expansion along major interstate highways. Srivastava et al. 2012 developed an online Geographic Information System (GIS) survey instrument that was used for collecting information from truck drivers about the locations of truck parking capacity shortages. The survey was restricted to 10 mid-Western states in the U.S., and 317 truck drivers participated. Their results showed that in the 10 mid-Western states reviewed, at least 21 truck parking facilities required a significant expansion to address capacity issues (Srivastava et al. 2012). Despite limited parking supply, providing the needed capacity all over the U.S is very expensive and would likely encounter local resistance (Boris and Johnson 2015). The results of these and other studies suggest that other methods of managing parking resources should also be explored beyond capacity expansion.

2.2. Previous Forecasting Research in Parking

One management strategy that has been recommended in the literature is implementing intelligent transportation systems that provide real-time parking conditions at truck stops (Parametrix 2005). In addition to providing users with information in real time and allowing them to make parking reservations in advance, those intelligent parking systems can also provide truck drivers with information about the forecasted parking use at specific hours of a day (Caicedo et al. 2012). Several different parking forecasting models have been explored in the literature. Burns and Faurot 1992 developed an econometric forecasting model from the revenues of two parking facilities in Kansas City. The model explained parking revenues in terms of the economic activity (retail employment) in the city, seasonal variations in parking demand, as well as certain facility specific events. The model had considerable power in explaining the observed revenues from the parking facilities. Caicedo et al. 2012 took a somewhat different approach in forecasting parking use. The authors developed a methodology that consists of three main steps to forecast parking availability. First, a discrete number of parking requests was simulated during a given time period. Next, a discrete choice model was employed to distribute the requests among the possible parking alternatives based on several attributes. Finally, the parking forecast for a given facility was computed using the number of parking requests simulated and the number of departures that are expected to take place between the time the requests were made and the time for which the forecast is made (Caicedo et al. 2012). Heinitz and Hesse 2009 developed a time-dependent truck parking demand model for facilities along a Federal Highway. The model serves as a decision-support system for target-oriented improvements and tests various truck parking transport policy measures. Ji et al. 2014 developed a more data-driven approach in forecasting available parking spaces. The Pearson coefficient was used to measure the similarity between different days. Next, the Largest Lyapunov Exponent method was employed to determine the minimum number of days that should be included in the training dataset to fully capture the chaotic behavior of the time series. While results showed that the largest Lyapunov Exponent method provides accurate predictions over the long term, truck drivers are usually interested in knowing how the parking availability will look in the next few hours.

2.3. Short-Term Forecasting Techniques

Short-term forecasting techniques can be classified into four main categories in the literature: 1) Statistical Techniques, 2) Artificial Intelligence Techniques, 3) Knowledge-Based Expert Systems, and 4) Hybrid Techniques. While different techniques have proven to be successful in different applications and circumstances, Artificial Neural Networks (ANNs) have recently received much attention, and a large number of papers have reported successful experiments and practical tests employing them. To name a few, Kiartzis et al. 1995 presented an ANN model for short-term load forecasting. The inputs to the model are load profiles of the previous two days and the minimum and maximum temperature forecasts. The authors showed that the model is capable of providing 24-hour forecasts at an instant with a 2.66 % average absolute forecast error when applied to data from a Greek interconnected power system. In another study, Srinivasan et al 1994 developed an ANN for a similar application. However, the only model inputs are past loads, and the output is the load forecast for a given day. The authors reported an average percent error ranging between 1.6% and 2.4%, depending on the number of neurons used and the season of the year. While these are just a few early studies highlighting the success of ANN in short-term forecasting applications, many more recent studies also verify its success. The reader is referred to (Hippert et al. 2001; Baliyan et al. 2015) for a detailed review.

Although ANNs have proven to be successful in short-term forecasting applications, they have a few limitations and drawbacks in the context of forecasting truck parking occupancy in real time. First, they are known to be computationally expensive. Moreover, the development of ANN models is very complicated and can take long periods of time. In this paper, we propose a short-term forecasting algorithm based on Fourier Transformations that is much faster than ANNs, easier to develop, and provides roughly the same prediction accuracy as ANNs. The developed model is discussed next.

3. Methodology

In this section, we describe the Fourier forecasting model that we developed to predict truck parking occupancy. The process involved three main stages. In the first stage, we conducted exploratory data analysis to detect any cyclic trends intrinsic in the time series. After detecting recurrent behaviors, we fit a Fourier model to the average behavior of a particular day and used the model to forecast the truck parking occupancy. Then, as the day proceeded and new real-time data became available, we computed the forecast error and applied mixed correction methods to the forecast when the error exceeded a specified threshold. We discuss each of the steps below.

3.1. The Data

The data used in this analysis are derived from a trucking logistics facility on I-5 in the northern San Joaquin Valley of California. The facility is not a traditional truck stop, in that it does not have amenities such as restaurants or a convenience store, but it accepts trucks for parking as well as container storage. The facility manages demand through an inventory system where truck drivers check-in with staff that is on-site upon entry and exit. This produces a very accurate human sensing of the facility, as it is effectively a spot-specific sensing system. The total count of parked vehicles is known at all times. The facility normally holds between 600 to 650 trucks/trailers, but can have an upper capacity of about 800 if needed. The facility allowed researchers to ping the total inventory of vehicles every minute, which produced a continuous time series of activity spanning a whole year.

3.2. Exploratory Data Analysis

Using these data, we plotted the activity at the facility for each day in the year of 2016. The plots are shown in Fig. 1, with each subplot corresponding to a particular weekday. The x-axis -- labeled as “Hours” -- reflects the time of day, where time 0 refers to the start of the day (00:00) and time 24 refers to the end of the day (24:00). The y-axis -- labeled as “Week Number” – corresponds to the week number in that year. The z-axis -- labeled as “Indexed Truck Parking Occupancy” -- represents the truck parking occupancy at the facility at a particular day and time. Note that the occupancy was indexed to 1 for scaling and visualization purposes.

We explored all visuals, and two key findings were detected. First, similar days from different weeks exhibited similar truck parking activity with slight variations toward the end of the day. Second, four distinct trends were observed for any weekday, and a fifth trend applied to weekends. Examples of these trends are presented in Fig. 2, and we define all these trends below:

- **The Regular Trend**: This was the most common trend across all weekdays and represented a time series that starts at a stable occupancy during midnight then gradually declines during the morning when trucks leave the logistics facility. It then stabilizes during noon to afternoon hours. In the evening, it gradually increases back to around the same initial occupancy a few hours before midnight. A total of 161 weekdays in the year of 2016 were identified to follow a regular trend.

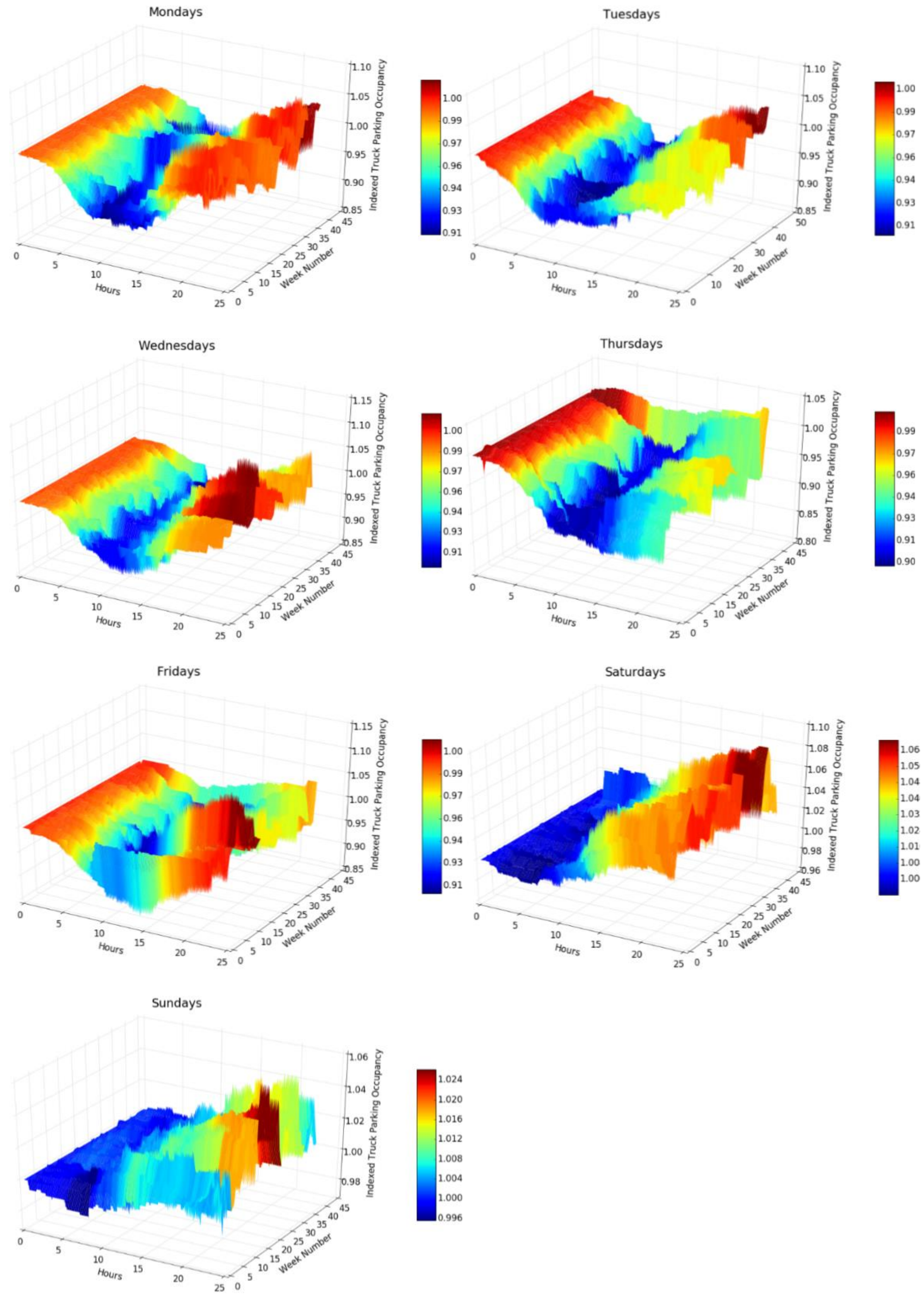

Fig. 1 Exploratory Data Analysis (the color bar indicates the value of the indexed truck parking occupancy)

- **The Surplus Trend**: This trend has similar characteristics to the regular weekday trend except that, during the nighttime, the net arrival rate to the logistics facility is higher than the regular trend. Also, the occupancy at the end of the day is significantly greater than the initial occupancy, and thus the name “surplus.” A total of 24 weekdays in the year of 2016 were identified to follow a surplus trend.

- **The Discharge Trend**: This trend also has similar characteristics to the regular weekday trend with the exception that once the time series stabilizes around noon, it does not pick up again throughout the entire day. This causes the occupancy at the end of the day to be significantly lower than the initial parking occupancy and thus the name “discharge. A total of 32 weekdays in the year of 2016 were identified to follow a discharge trend.

- **The Holiday Trend**: The truck parking activity for days corresponding to national holidays were tracked and observed individually. Our visualizations showed that those days exhibited a stable parking occupancy throughout the whole weekday. Hence, national holidays were eliminated from the dataset.

- **The Weekend Trend**: Weekend days exhibited a separate pattern apart from the weekday trends outlined above. While forecasting on weekends was deemed a less pressing need for truck drivers, we determined that a separate model was best used for weekend forecasting. For the subsequent analysis and results, we focus primarily on weekdays.

It is important to note that the classification of weekdays into Regular, Surplus, or Discharge Trends was conducted based on the value of the normalized truck parking occupancy at the end of the day. Any weekday that had a normalized truck parking occupancy that is 1.025% or greater than the start of the day was classified as Surplus, whereas any weekday that had a normalized truck parking occupancy that is 0.95% or lower than the start of the day was classified as Discharge. All other weekdays were classified as Regular. While this classification technique is specific to the dataset and the thresholds may vary from one facility to another, it nonetheless is rather simple and easy to implement after a data exploration has been conducted, and it does a good job in classifying the different trends. Other techniques such as time-series clustering algorithms may be explored in future research.

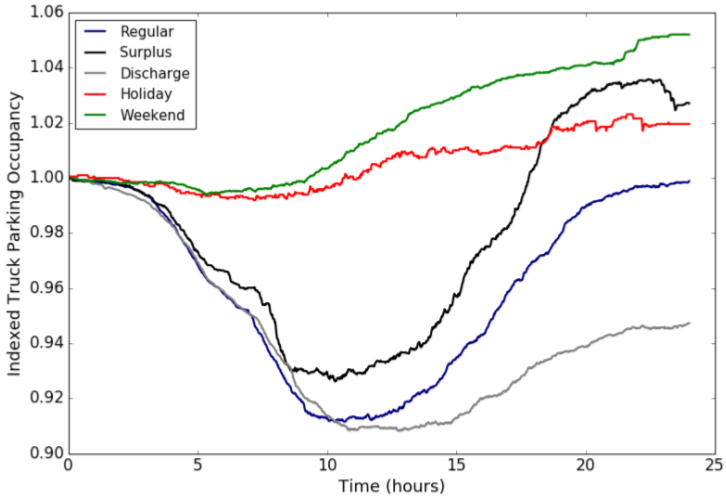

Fig. 2 Common Daily Trends

3.3. Statistical Description of Normalized Truck Parking Occupancy

Fig. 3 displays the hourly distribution of the normalized truck parking occupancy of each weekday trend in year 2016 in boxplot format. As can be observed from Fig. 3, the normalized truck parking occupancy does not seem to vary from one trend to another during early hours of the day (from 12 AM till around 10 or 11 AM). However, it is clear that the three trends diverge considerably in the afternoon period, highlighting the need of using different prediction models based on the trend of the weekday to be forecast.

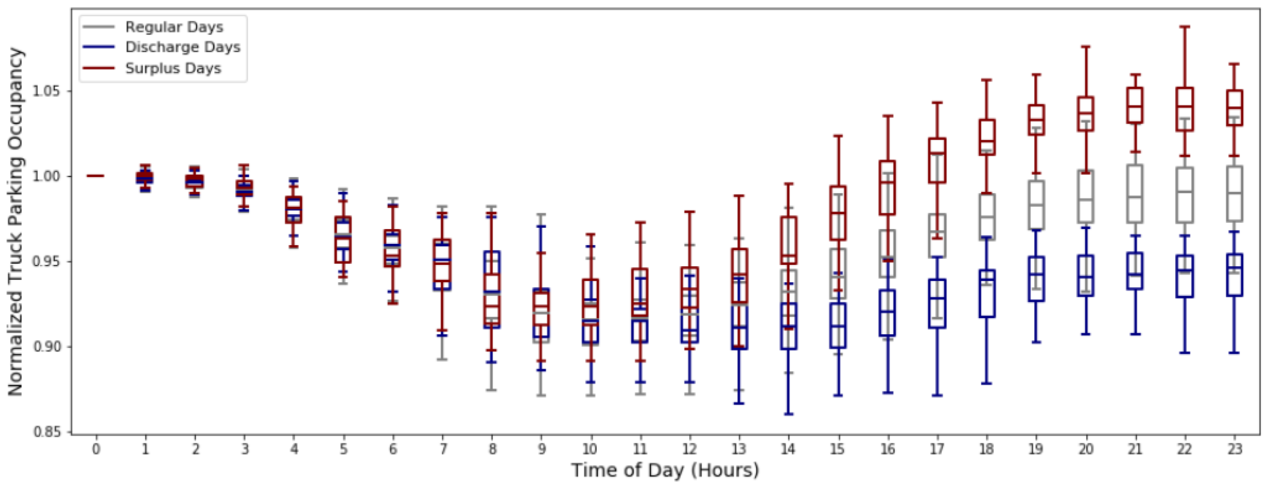

Fig. 3 Hourly Distribution of Normalized Truck Parking Occupancy

3.4. The Discrete Fourier Transform

The Fourier model is developed by first applying a Discrete Fourier Transform (DFT) to a time series object. In our case, the time series object is the indexed time series of a given day of activity. The DFT takes any discrete time-based pattern and decomposes it into a sum of sinusoidal functions. Each sinusoidal function is defined by three parameters: 1) its frequency, 2) amplitude, and 3) phase. After the parameters are estimated for each sinusoidal function present in the discrete time-based pattern, the sinusoids are aggregated to develop the Fourier Series or the Fourier model.

To begin with, the time series object is converted from the time domain to the frequency domain. This transformation is accomplished by applying Equation 1 shown below:

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N} \quad (1)$$

Where N represents the number of time samples in the time-series object, n is the current point in time being considered, x_n is the truck parking occupancy at time n, k is the index of the frequency bin being considered, and X_k is the "amount" of frequency k in the time series object (a complex number). Equation 1 simply sums up the contribution to a particular frequency bin k from each time spike in the time domain. For simplicity, we represent the component $2\pi kn/N$ as b_n hereafter. Expanding Equation 1 will result in the series shown in Equation 2:

$$X_k = x_o \cdot e^{-ib_o} + x_1 \cdot e^{-ib_1} + \cdots + x_{N-1} \cdot e^{-ib_{N-1}} \quad (2)$$

According to Euler's formula, any exponential function raised to the power of a complex number can be expressed as a sum of sine and cosine functions as shown in Equation 3:

$$e^{ix} = cos(x) + i \cdot sin\,(x) \quad (3)$$

Substituting Equation 3 into Equation 2 will result in the expression shown in Equation 4:

$$X_k = x_o \cdot [cos(b_o) + i \cdot sin(b_o)] + x_1 \cdot [cos(b_1) + i \cdot sin(b_1)] + \cdots + x_{N-1} \cdot [cos(b_{N-1}) + i \cdot sin(b_{N-1})] \qquad (4)$$

Equation 4 shows that X_k is essentially the sum of a real valued number and a complex valued number. Let A represent the real valued number and B represent the complex valued number. Then, the magnitude of the frequency bin k can be calculated using Pythagoreans theorem as shown in Equation 5:

$$a_k = \sqrt{{A_k}^2 + {B_k}^2} \qquad (5)$$

Where $a_k$represents the magnitude of the frequency bin k. The magnitude of the frequency is basically the amplitude of the sinusoid at that frequency. Furthermore, the phase of the sinusoid can be calculated using Equation 6:

$$\theta_k = tan^{-1}\left(\frac{B_k}{A_K}\right) \qquad (6)$$

Where θ_k is the phase of the sinusoid at frequency bin k. The above equations were applied to all possible values of k, $\forall\ k = 0, 1, 2, 3, \ldots, N-1$ Hertz. Finally, the Fourier model was reconstructed by aggregating all the detected harmonics, as shown in Equation 7 below:

$$F(t) = \sum_k a_k \cdot cos\ (2\pi kt) + \theta_k \qquad (7)$$

Where $F(t)$ is the predicted truck parking occupancy at time t.

3.5. The Static Regular Model: Average Behavior of a Regular Day

We introduce a forecast that we call the “Static Regular” model, which is based on the assumption that the day-to-be-forecast fits a regular trend, and there is no update from the initial prediction at the beginning of the day. That is, the Static Regular model makes a single prediction at the start of the day and considers no new information as the day proceeds to update the forecast.

The Static Regular model is built on the observation within Fig. 1 that most weekdays exhibit some common behavior. That is, Mondays are similar to other Mondays, and Tuesdays are similar to other Tuesdays. Furthermore, most (but not all) days fit closest to the form of the regular trend, which presents a good initial estimate of likely occupancy patterns during the day. The time series diverges over the course of the week, but in practice this can be corrected by recalibration overnight, when traffic is traditionally low. Collectively, these observations suggest more generally that: 1) truck parking occupancy for a given day during the week can be forecast using the time series of the same day from previous weeks, and 2) the forecast deviation that accumulates across contiguous days can be eliminated by a daily recalibration of the time series to the observed level of the parking occupancy at midnight (or some nearby time) of each day.

To estimate the Static Regular model for a given day, the same weekday from the previous four weeks that exhibited the regular trend were used for training the Fourier model (e.g., four previous regular Tuesdays to forecast the upcoming Tuesday).

Each regular time series object from previous weeks is indexed to a value of 1 to establish a common starting value with changes relative to each other over 24 hours. The indexed time series objects are then averaged at each minute interval to produce a single time series object reflecting the average activity over the past four regular weekdays. Next, the average time series object is used to develop the Fourier model defined earlier. The Fourier model is then used to predict the truck parking occupancy for the entire target day of the forecast.

Since the model was developed using an indexed time series object, the predictions made by the model were in the form of indexed values, which by themselves are not useful to truck drivers. To translate the values back into parking occupancy predictions, the indexed prediction series is multiplied by the known value of parking occupancy at the start of the target day for the forecast. For the Static Regular model, this prediction is fixed for the day and assumes a regular trend with no updating based on activity during the target day. These limitations are addressed in the following sections.

3.6. Trend Switching Model Based on Activity of the Day

As discussed earlier, some days can exhibit surplus or discharge trends. Without intervention, the Static Regular model can become rather inaccurate when the day departs significantly from the fitted regular trend. But in practice, these forecasts can be updated once active model computations suggest that the day's activity is not going to follow the fitted regular trend. The Trend Switching Model is built on the premise that continuous assessment of the initial forecast error can permit computations to guess that the trend of the day will not fit the regular trend. Once this happens, the forecasted trend can be switched to predict patterns based on the historical discharge or surplus trends, depending on the direction of the known error.

Trend switching is implemented when the error exceeds a minimum threshold and is sustained for an extended time period. If the forecast error at a given point in time is positive (e.g., actual parking occupancy is greater than the forecasted parking occupancy) and the error has been increasing for the past 30 minutes, then there are two possible scenarios: 1) the actual time series is decreasing at a rate lower than the forecasted time series or 2) the actual time series is increasing at a rate higher than the forecasted time series. The first scenario is likely to occur during the time at which trucks depart from the parking station early in the morning. The exploratory data analysis showed that during this period, the three common trends do not vary significantly (e.g., they all decline in the morning).

Therefore, the forecast errors, for the morning period, are expected to be insignificant when using the Static Regular model, regardless of whether the day in fact exhibits a surplus or discharge trend. Therefore, the minimum error threshold has to be sufficiently large and sustained to indicate that the day is following a new pattern. In the case of this dataset, we found that a sustained error of 15 trucks or more over 30 minutes was sufficient to suggest that the day was likely following a different (non-regular) trend. Naturally, these values are facility specific and subject to the capacity of a parking lot.

If these conditions were met and the error was positive, we would apply the previous four surplus trends of the same weekday as a training dataset. Using the same procedure described earlier, a curve is fit using the Fourier model to the training surplus data. Because the day has already progressed for some time, the new surplus trend predictions are linked to the point in time when the observed error model switching condition was triggered. If the forecast error was negative (e.g., actual parking occupancy is lower than the forecasted parking occupancy) and the switching conditions were met, then the previous four discharge trends of the same weekday were used as the training dataset to estimate the discharge trend.

3.7. Trend Shifting Model Due to Sustained Error

The trend switching mechanism can improve the forecasts made by the Static Regular model, and it is motivated by the fact that activity can sometimes follow trends that are significant departures from the general shape of the regular trend. However, there are additional error-correction steps that can be derived from real-time data. Further improvements can be made by correcting errors that are observed to occur, even when the predicted trend is revised to correctly reflect the activity as fitting the discharge or surplus trend. If pre-defined error conditions are met, the Trend Shifting Model simply re-aligns the existing forecast with observed activity. It keeps the same trend, so the initial prediction of a regular trend remains a regular trend. For this approach, we use the same error condition as defined with the Trend Switching model. If an error of 15 trucks or more is sustained for 30 minutes, the forecasted time series is shifted to the value of the actual time series at the present time, while still maintaining the same trend for subsequent predictions through the remainder of the day.

3.8. Hybrid Model

The Hybrid model combines the error correction techniques applied by the Trend Switching and Trend Shifting Fourier models. It is motivated by the fact that on some days, the actual occupancy might continue to deviate from the predicted occupancy, even after switching the predicted trend from Regular to Surplus or Discharge. The Hybrid model works as follows: First, it checks if any of the defined Trend Switching errors are observed and updates the trend accordingly. Then, it continues to monitor the observed truck parking activity, searching for any errors that would trigger the Trend Shifting mechanism. Similar thresholds are used to what was previously defined.

3.9. Summary of Models

Thus far, we have explained the forecasting methods for predicting activity based on the following approaches:

- **Static Regular Model**: A prediction based on the most recent weekdays exhibiting a regular trend of behavior with no consideration of new information from the day.

- **Trend Switching Model**: A prediction that begins as the regular trend but switches the predicted trends to surplus or discharge, if predefined error conditions are met using updated data throughout the day.

- **Trend Shifting Model:** A prediction that shifts the existing trend to match observed data (at the time that the error conditions are met), if pre-defined error conditions are met. However, it does not change the predicted trend.

- **Hybrid Model**: The Hybrid model is a mix of error correction mechanisms. A prediction that first adjusts the trend based on the Trend Switching Model, but if the error conditions continue to be met later in the day, applies the Trend Shifting Model until the end of the day.

Fig. 4 presents an overall summary of the process that is applied to implement the forecast. In each model, the Static Regular model is used to predict activity for the entire day at 12 AM. Different models then engage in various error correction approaches based on consideration of activities throughout the day. We explore the accuracy of these four models in the following section.

Exploratory Data Analysis

1) Plot activity for each day of the year.
2) Identify common patterns and cyclic trends in activity. This analysis found 4 unique common weekday patterns, but other environments might have a different number of common patterns.
3) Classify all days in the dataset into one of the specific categories of identified trend-types.
4) Index each day such that the starting value of occupancy is equal to 1.

Fourier Modeling

1) Identify the day-to-be-forecast.
2) Identify indexed time series of the previous four day-of-week weekdays (e.g., past four Mondays) that are classified as Regular Trends.
3) Average these four identified trends minute-by-minute to produce a single trend that is the average behavior of the past four days.
4) Train the model by applying the Discrete Fourier Transform to this average indexed series.
5) Translate the predicted trend back to a trend of real occupancy by multiplying the index series by the actual parking occupancy at the beginning of the day. This is the Static Regular Model output.

Error Correction (Trend Switching, Shifting, Hybrid models)

1) Evaluate each minute whether the observed model departs from predicted output of the Static Regular Model.
2) If the defined error threshold is exceeded for a predefined but continuous period of time, implement an error correction measure, which in this case could be trend switching and/or shifting, depending on the model implemented.

Fig. 4 Process Flow of the Forecast Implementation

4. Results and Discussion

In this section, we discuss the performance of the different models we tested and summarize the prediction results using the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) metric.

4.1. Prediction Error Discussion

To visually illustrate the different predictions, Fig. 5 shows the actual and forecasted occupancy with each model, for a selected week in 2016. Fig. 5 (a) displays the forecasts made by the Static Regular Model, whereas

Fig. 5 (b), (c), and (d) display the forecasts made by the Trend Switching, Trend Shifting, and Hybrid models, respectively. Fig. 5 (e) shows the forecast errors, which are computed as the actual occupancy minus the predicted occupancy, for each stage of the forecasting process.

Fig. 5 (a) is just an example of one illustrative week, and it shows that the Static Regular model can sometimes be quite good, while at other times can provide inaccurate forecasts if activity follows a non-regular trend. On Wednesday, for example, actual occupancy follows a surplus trend, and it ends significantly higher than was predicted at the beginning of the day. The Trend Switching model, shown in Fig. 5 (b), corrects for this by allowing the prediction to be “switched” from the regular trend to the surplus trend. This switching occurs midday on Wednesday and changes the predicted trend for the remainder of the day. It then follows the actual occupancy far better, although it over predicts occupancy at the end of the day.

While the Trend Switching model effectively corrects for the large prediction error shown on Wednesday, it also causes an end-of-the day error on Monday that was not present with the Static Regular model. Fig. 5 (b) shows that the error conditions for switching the trend to discharge trend are met on Monday, and this results in a gross under prediction of the occupancy at the end of the day. Such a case visually illustrates the trade-offs of error correction models, where fixed rules defining when corrections are applied can make things worse on a case-by-case basis. Fig. 5 (c) shows the predictions made by the Trend Shifting model, which simply shifts the forecast made by the Static Regular model to the actual value of occupancy when the error meets the pre-conditions defined earlier. This model makes no change to the trend predicted by the Static Regular model but continually corrects the position of the trend when the error conditions are met.

(e)

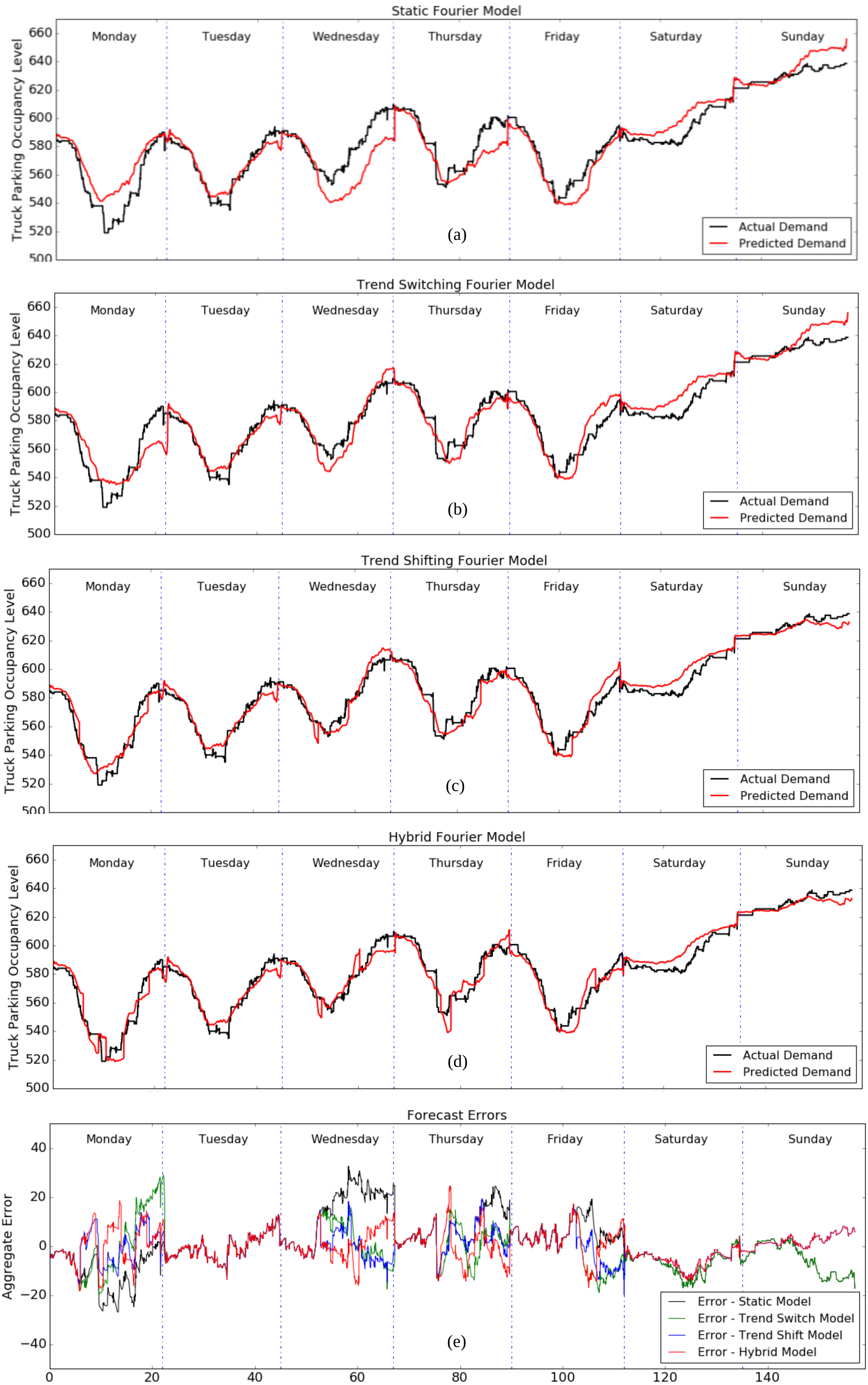

Fig. 5 Actual vs. Predicted Occupancy

The Hybrid model, combining the approaches of both the Trend Switching and Trend Shifting models, is shown in Fig. 5 (d). During this particular week, it performs similarly well to the Trend Shifting model but not notably better. In some cases, the rules of the Hybrid model cause such erratic departures not present in the other predictions that are then corrected by error conditions triggering a shift back to observed activity. Fig. 5 (e) plots the forecast errors throughout the week for the four different models under analysis. Fig. 5 (e) shows that the maximum error is exhibited by the Static Regular model and the Trend Switching model, while the Trend Shifting and Hybrid models are generally lower with a maximum error of about 20 trucks. Note that Fig. 5 (e) also shows that there can be certain days (such as Tuesday) where the forecast errors are the same for all models. This indicates that, for those days, the Static Regular model produced predictions at the start of the day that were accurate enough, such that the error correction conditions were never triggered.

Fig. 5 represents the perspective of evaluating the models after the error corrections and model adjustments have been applied at the end of the day or week. However, the results do not show a truck driver's perspective, which would reveal larger errors. For example, if at the beginning of a given day, a truck driver checks the forecast for an 8:00 PM arrival, s/he may see occupancy to be predicted as 575. As the truck driver drives toward the location, new data points are being collected, and the model adjusts the predictions according to one of the correction mechanisms. This causes the model to adjust the 8:00 PM occupancy prediction to 611 when the actual occupancy turns out to be 625 at 8:00 PM.

When evaluating the forecast error from the final error-adjusted prediction (as shown in Fig. 5), the error will appear to be 14 trucks. However, when evaluating the forecast error from the perspective of the truck driver's initial query of the forecast, the error will be 50 trucks. Hence, the prediction performance is a function of the query time.

To truly measure the performance of the prediction models, the forecast errors must be analyzed from the truck driver's perspective and over the entire dataset (not just a selected week). We calculated the RMSE for each day based on the minute-by-minute error experienced by the truck driver. For example, to calculate the error experienced by the truck driver for an occupancy prediction at 8:00 PM, we assumed that the 8:00 PM forecast was checked at every minute before 8:00 PM and the forecast error at each minute of the observation was recorded and then averaged. This average error constitutes the average forecast error experienced by the truck driver up to

8:00 PM. We applied this procedure to every minute of the day, and we used the forecast errors for each minute to calculate the RMSE for the entire day over every day in the 2016 dataset.

4.2. Sensitivity Analysis of Training Days Assumption

Before providing a detailed summary of the forecasting results, it is important to evaluate an assumption adopted in the methodology to ensure robustness. Recall that when developing the regular, surplus, or discharge models, the previous "four" weekdays with a similar trend type were used for training. To evaluate this assumption, we tested the sensitivity of the average RMSE to the number of days used for training the Hybrid Model. The results of the sensitivity analysis are displayed in Fig. 6.

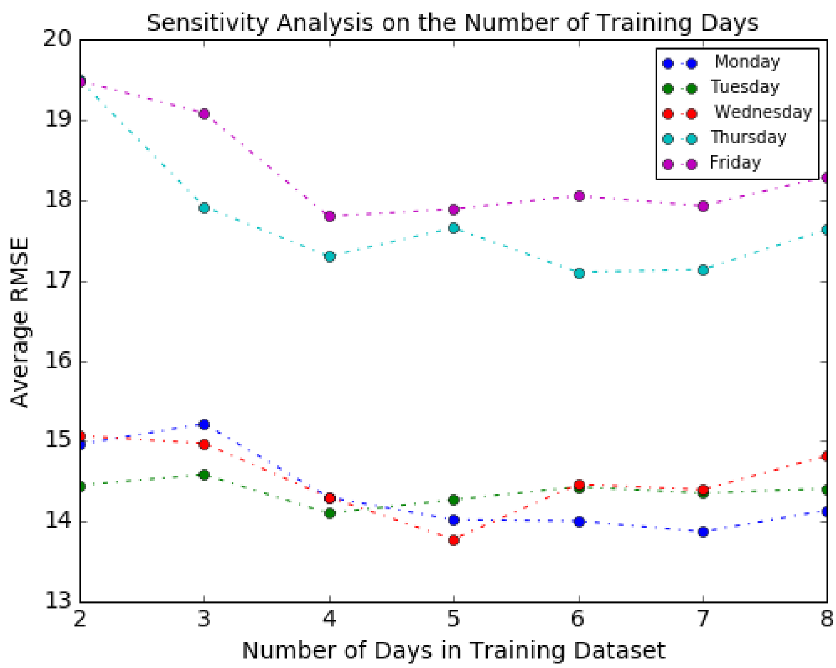

Fig. 6 Sensitivity Analysis of Training Days Assumption

Fig. 6 shows that the average RMSE across all weekdays is relatively insensitive to the number of days used for training. However, there is also a slight improvement in the forecasting accuracy across all weekdays when using four days as compared to two or three days. The results show effectively flat performance when increasing the number of days used. Since using fewer days is more efficient, the four similar days were applied for training.

4.3. *Summary of Results*

Table 1 displays the average RMSE and the standard deviation of the RMSE for each day of the week for the four different models. Table 1 shows that the Trend Shifting model results in the lowest average RMSE across all of the days of the week over the entire dataset. Furthermore, the Trend Shifting model has the lowest standard deviation for Tuesday, Friday, Saturday, and Sunday, whereas the Trend Switching model has the lowest standard deviation for Monday, Wednesday, and Thursday. However, averages can hide volatility. As another measure of performance, Table 2 displays the minimum and maximum RMSE for each day of the week for the four different models.

Table 2 shows that the RMSE for the days in 2016 can vary from two to 40 trucks when applying the Static Regular model, two to 29 trucks when applying the Trend Switching model, two to 31 trucks for the Trend Shifting model, and two to 39 trucks for the Hybrid model. Table 2 also shows that for Monday, Tuesday, Wednesday, and Friday, the Trend Switching model results in the lowest maximum RMSE. In contrast, for Thursday, Saturday, and Sunday, the Trend Shifting model results in the lowest maximum RMSE.

Table 1
Average RMSE and Standard Deviation for Each Day of the Week

		Static Regular	**Trend Switching**	**Trend Shifting**	**Hybrid**
Monday	Average	14.6	14.3	**13.6**	14.3
	Standard Deviation	8.1	4.8	6.2	5.2
Tuesday	Average	13.7	12.9	**12.5**	14.1
	Standard Deviation	6.3	4.9	4.7	6.1
Wednesday	Average	14.8	14.3	**13.7**	14.3
	Standard Deviation	8.3	4.9	6.3	5.3
Thursday	Average	13.9	15.3	**13.2**	17.3
	Standard Deviation	5.9	4.5	4.7	6.6
Friday	Average	15.9	17.0	**14.0**	17.8
	Standard Deviation	8.5	6.1	6.0	7.5
Saturday	Average	8.6	-	**7.8**	-
	Standard Deviation	5.2	-	3.9	-
Sunday	Average	6.0	-	**5.7**	-
	Standard Deviation	3.2	-	2.6	-

Table 2
Minimum and Maximum RMSE for Each Day of the Week

		Static Regular	Trend Switching	Trend Shifting	Hybrid
Monday	Minimum	4.5	4.9	4.5	4.9
	Maximum	39.5	**24.7**	31.1	30.1
Tuesday	Minimum	4.3	4.3	4.3	4.3
	Maximum	35.4	**24.0**	26.1	34.4
Wednesday	Minimum	4.5	4.9	4.5	4.9
	Maximum	39.5	**24.7**	31.1	30.1
Thursday	Minimum	4.8	7.8	6.5	8.6
	Maximum	31.8	27.0	**25.9**	38.2
Friday	Minimum	4.0	7.9	4.0	8.1
	Maximum	37.1	**29.4**	30.3	38.9
Saturday	Minimum	2.8	-	2.8	-
	Maximum	28.2	-	**20.3**	-
Sunday	Minimum	1.8	-	1.8	-
	Maximum	14.7	-	**12.6**	-

It is often beneficial to test the performance of an algorithm using more than one metric. **Error! Reference source not found.** displays the average MAPE and the standard deviation of the MAPE for each day of the week for the four different models. **Error! Reference source not found.** shows that the Trend Shifting model results in the lowest average MAPE across all days of the week, except for Wednesdays, where the Hybrid model performs slightly better. In terms of the standard deviation of the MAPE, the Trend Shifting Model exhibits the lowest standard deviations for Tuesdays, Wednesdays, and Thursdays, whereas the Hybrid Model provides the lowest standard deviation for Mondays and Fridays.

Error! Reference source not found. shows that the MAPE for the days in 2016 can range from around 0.25 to 7.00 when applying the Static Regular Model, 0.70 to 3.00 for the Trend Switching Model, 0.40 to 2.30 for the Trend Shifting Model, and 0.70 to 2.30 for the Hybrid Model. Note how the range of the MAPE significantly decreases when applying any of the error correction techniques. **Error! Reference source not found.** also shows that for Tuesdays, Thursdays, Fridays, Saturdays, and Sundays, the Trend Shifting model results in the lowest maximum MAPE, while the Hybrid Model provides the lowest maximum MAPE for Mondays and Fridays.

Table 3

Average MAPE and Standard Deviation for Each Day of the Week

		Static Regular	Trend Switching	Trend Shifting	Hybrid
Monday	Average	1.74	1.95	**1.60**	1.62
	Standard Deviation	0.70	0.20	0.14	0.06
Tuesday	Average	1.85	1.83	**1.65**	1.67
	Standard Deviation	0.81	0.24	0.18	0.22
Wednesday	Average	1.93	1.97	1.69	**1.65**
	Standard Deviation	1.03	0.29	0.11	0.16
Thursday	Average	1.93	2.09	**1.53**	1.89
	Standard Deviation	0.86	0.10	0.11	0.15
Friday	Average	2.22	2.29	**1.82**	1.94
	Standard Deviation	1.21	0.37	0.28	0.19
Saturday	Average	1.19	-	**1.02**	-
	Standard Deviation	0.73	-	0.10	-
Sunday	Average	0.75	-	**0.63**	-
	Standard Deviation	0.37	-	0.33	-

Table 4

Minimum and Maximum MAPE for Each Day of the Week

		Static Regular	Trend Switching	Trend Shifting	Hybrid
Monday	Minimum	0.79	1.76	1.49	1.42
	Maximum	3.92	2.55	2.19	**1.74**
Tuesday	Minimum	0.48	0.72	0.72	0.72
	Maximum	3.82	2.22	**1.81**	1.84
Wednesday	Minimum	0.77	1.14	1.33	1.21
	Maximum	5.17	2.36	1.86	**1.77**
Thursday	Minimum	0.56	1.79	1.23	1.58
	Maximum	5.12	2.44	**1.73**	2.07
Friday	Minimum	0.58	1.26	1.01	1.28
	Maximum	6.80	2.96	**2.23**	2.26
Saturday	Minimum	0.32	-	0.85	-
	Maximum	3.44	-	**1.27**	-
Sunday	Minimum	0.24	-	0.39	-
	Maximum	2.03	-	**1.61**	-

The results provided in Table 1 and Table 2 suggest that the Switching and Shifting models perform better than the Static Regular and Hybrid models across all the RMSE performance measures. Although the Trend Shifting model results in the lowest average RMSE across all the days of the week, it provides a higher maximum RMSE than the Trend Switching model on several days of the week.

Furthermore, the results provided in **Error! Reference source not found.** and **Error! Reference source not found.** suggest that the Trend Shifting and Hybrid models perform better than the Static Regular and Trend Switching models across all the MAPE performance measures. Also, the Trend Shifting model tends to provide the lowest average MAPE and the lowest maximum MAPE across most of the days. All things considered, we deem the Trend Shifting model is the best model for forecasting with this dataset. Next, we compare the accuracy of the Trend Shifting Fourier Model with an ANN.

4.4. Comparison with Neural Networks: Accuracy and Efficiency

This section compares the accuracy of the Trend Shifting Fourier model to a baseline model commonly used in recent literature for multi-step ahead time-series forecasting: the Long-Short Term Memory Recurrent Neural Network (LSTM-RNN) (Tian and Pan 2015; Yunpeg et al. 2017; Petnehazi 2019). The core concept behind the LSTM-RNN is to include an iterative structure in the hidden layer of the RNN that captures the long-term dependencies in the time-series. To develop the LSTM-RNN model, a sequential class was first instantiated, and four LSTM layers with 50 neurons were then added to the model along with four dropout layers to prevent over-fitting. Finally, a dense layer was added to make the model more robust. Note that a unique model was developed for each weekday (Monday through Friday).

Next, to estimate these models, "feature" matrices and "label" columns were developed for each weekday. Each row or observation in the "feature" matrix contained scaled minute-by-minute truck parking occupancy data pertaining to the previous four weekdays of the day to be forecasted, and each row or observation in the "label" column contained scaled minute-by-minute truck parking occupancy data of the day to be forecasted. The feature matrices and label columns of each weekday were then split into training and testing sets using a 67%-33% split, respectively. Each LSTM-RNN model was estimated using the training set of the corresponding weekday and was trained for a duration of 100 epochs while using a mean-squared error loss function. The trained models were then used to forecast the occupancy of the weekdays in the testing set. Table 5 compares the accuracy of the LSTM-RNN model with the Trend Shifting model in terms of the RMSE and MAPE metrics.

4.4.1 Accuracy: RMSE

We begin the comparison between the two models by analyzing the average RMSE. As can be observed from Table 5, the Trend Shifting Fourier model performs better than the LSTM-RNN model in all weekdays,

Table 5

Accuracy Comparison: LSTM-RNN vs. Trend Switching Fourier Model

		RMSE			MAPE		
		LSTM-RNN	Trend Shifting	% Decrease	LSTM-RNN	Trend Shifting	% Decrease
Average	Monday	14.72	13.60	**7.64**	1.97	1.60	**18.82**
	Tuesday	11.14	12.50	-12.18	1.46	1.65	-12.82
	Wednesday	13.73	13.70	**0.25**	1.85	1.69	**8.49**
	Thursday	18.92	13.20	**30.22**	2.71	1.53	**43.48**
	Friday	16.88	14.00	**17.05**	2.39	1.82	**23.72**
Standard Deviation	Monday	5.30	6.20	-16.88	0.78	0.14	**82.01**
	Tuesday	5.09	4.70	**7.70**	0.69	0.18	**73.98**
	Wednesday	5.69	6.30	-10.75	0.69	0.11	**84.08**
	Thursday	10.10	4.70	**53.45**	1.41	0.11	**92.18**
	Friday	8.14	6.00	**26.33**	1.04	0.28	**72.98**
Minimum	Monday	6.70	4.50	**32.84**	0.64	1.49	-133.37
	Tuesday	4.20	4.30	-2.27	0.77	0.72	**5.97**
	Wednesday	5.15	4.50	**12.68**	0.89	1.33	-48.73
	Thursday	6.32	6.50	-2.83	1.10	1.23	-11.70
	Friday	7.78	4.00	**48.57**	1.10	1.01	**8.28**
Maximum	Monday	29.07	31.10	-6.99	2.84	2.19	**22.80**
	Tuesday	21.70	26.10	-20.26	3.12	1.81	**41.92**
	Wednesday	28.67	31.10	-8.46	5.72	1.86	**67.51**
	Thursday	46.08	25.90	**43.79**	4.64	1.73	**62.74**
	Friday	33.34	30.30	**9.13**	4.64	2.23	**51.97**

except for Tuesday. In terms of the standard deviation of the RMSE, the Trend Shifting Fourier model performs better on Tuesday, Thursday, and Friday, whereas the LSTM-RNN performs better on Mondays and Wednesdays. As for the minimum RMSE, the Trend Shifting Fourier model performs better on Mondays, Wednesdays, and Fridays, whereas the LSTM-RNN performs better on Tuesdays and Thursdays. Finally, in terms of the maximum RMSE, the Trend Shifting Fourier Model performs better on Thursdays and Fridays, whereas the LSTM-RNN model performs better on Mondays, Tuesdays and Wednesdays. According to the above observations, there isn't a specific model that performs better than the other in all cases. On some weekdays, the Trend Shifting Fourier Model may provide more accurate predictions than the LSTM-RNN, and on other weekdays, the LSTM-RNN may perform better. However, it is worth noting that on Thursdays and Fridays the Trend Shifting Fourier model performs significantly better than the LSTM-RNN model across all RMSE metrics, except for the minimum RMSE of Thursday. This observation is important since our exploratory data analysis (see Fig. 1) shows that the majority of the Surplus and Discharge trends occur on Thursdays and Fridays. The fact that the Trend Shifting Fourier model performs significantly better on these days emphasizes that the LSTM-RNN model doesn't perform as well when predicting the truck parking occupancy of weekdays with a Surplus or Discharge trend. A discussion of the MAPE results is provided next.

4.4.2 Accuracy: MAPE

As can be observed in Table 5, the Trend Shifting model results in a lower average MAPE across all weekdays, except for Tuesday, and also exhibits a lower MAPE standard deviation across all weekdays. As for the minimum MAPE, the Trend Shifting Fourier model performs slightly better on Tuesdays and Fridays, whereas the LSTM-RNN model performs significantly better on the remaining weekdays. Finally, in terms of the maximum MAPE, the Trend Shifting Fourier Model performs significantly better across all weekdays. The fact that the LSTM-RNN performs considerably better in terms of the minimum MAPE, but significantly worse in terms of the maximum MAPE is also a very interesting finding. This highlights that on some days that can be characterized by a Regular trend, the LSTM-RNN can provide very accurate truck parking occupancy predictions, perhaps even more accurate than those provided by the Trend Shifting model, but when the occupancy trend departs from the Regular trend, as observed with the Surplus or Discharge trends, the model cannot provide predictions as accurate as the Trend Shifting model. Based on the above results and discussion, we deem the Trend Shifting Fourier model to be more accurate for the truck parking forecasting application considered in this paper.

4.4.3 Computational Efficiency

This section compares the computational efficiency of the Trend Shifting Fourier Model with the LSTM-RNN. It is important to remind the reader at this point that the LSTM-RNN is trained offline but used to make predictions online, whereas the Trend Switching Fourier Model is both trained and used to make predictions online. With the above in mind, it is reasonable to compare the computational efficiency of both models by observing the computation time required to train the Trend Shifting Fourier Model and use it to make predictions against the computation time required by the LSTM-RNN to make predictions. The aforementioned computational time metrics were recorded while making predictions for the entire dataset and a summary of the results are provided in Table 6. As can be observed in Table 6, the Trend Shifting Fourier Model outperforms the LSTM-RNN in terms of computation time across all weekdays. This further motivates the use of the Trend Shifting Fourier Model for the truck parking occupancy forecasting application considered in this work.

Table 6

Computational Efficiency of Trend Switching Fourier Model vs. LSTM-RNN

Computation Time (s)	Monday	Tuesday	Wednesday	Thursday	Friday
LSTM-RNN	20.73	15.37	14.73	16.50	14.45
Trend Switching Fourier Model	5.52	3.82	4.34	5.14	5.99
% Improvement	73%	75%	71%	69%	59%

5. Conclusion and Discussion

In this paper, we present several methods for forecasting truck parking exclusively using truck occupancy activity data from a facility on the I-5 corridor of California. The location and the data were well suited for an exploration of these methods because they provided a rare opportunity to use highly accurate occupancy data, as derived from a well-maintained inventory system over an entire year.

The results of the model show that even with highly accurate occupancy data and the reliable curve fitting of Fourier models, forecasting still presents a number of challenges and uncertainties. The performance of the prediction is ultimately a function of a number of subjective decisions regarding which training data to use (e.g., number of weekdays behind the target day), as well as the conditions that trigger error correction actions. Adjustments to these parameters can change the performance of the prediction and sometimes in unexpected ways. For example, in some cases, the use of more extensive historical data can make predictions worse, as can certain error correction rules as applied in specific conditions.

The Trend Shifting model performed the best in this analysis, even when considering the perspective of a truck driver checking the prediction well in advance of arrival to a location. This model performed better than the baseline Static Regular model because it proactively reacted with a correction when the error became large and sustained. At the same time, the basic curve fitting of the Static Regular model performed rather well by itself, given that it made no corrections for 24 hours. These results suggest that Fourier modeling is well suited for the practice of developing predictions of cyclical activity like truck parking. Nevertheless, this study has a number of limitations.

While the data used for modeling was of high quality, high-time resolution, and highly accurate, it reflects conditions not present in typical state-of-the-art truck parking data. That is, truck parking sensing is usually performed by equipment, not a rigorous inventory system, and is subject to its own error. Forecasting truck parking at a conventional truck stop would introduce additional complications that result from error in the occupancy data, which were not considered in this analysis. As sensing technology improves, the impact of this complication on forecasting performance may diminish. Furthermore, the rules applied to error correction of forecasts are somewhat arbitrary and their appropriateness is subject to the size of the truck stop. The error rule of 15 trucks sustained over 30 minutes, as applied in this study, is small for a lot of this facility's size and is a somewhat subjective value for the assessment of prediction performance. We could have designed the prediction model to correct itself every minute (shifting to the actual value, as soon as its off), but this would not allow us to truly evaluate how the predictions would perform in practice, where a truck driver would hardly be expected to update his or her knowledge at such a frequent rate. Inevitably, practical considerations in the science and art of forecasting need to be considered when applying methods and rules for intervention.

The broader motivation for this study is to evaluate the performance and feasibility of forecasting truck parking occupancy with the ultimate objective of improving the provision of truck parking availability information for truck drivers. Truck parking availability information in the near present is useful, but accurate predictions of truck parking within 24 hours and beyond would offer truck drivers even more data to inform sound parking decisions. Ultimately, the application of these or similar methods requires greater dissemination of truck parking sensing, which is still an area of active development. This research contributes to that effort by advancing the goal of employing data to produce better information for a safer and more efficient freight transportation system.

6. Data Availability Statement

All data, models, and code generated or used during the study are available from the corresponding author by request (raw truck parking occupancy data, processed truck parking occupancy data, code used to train the Fourier Model and generate forecasts, and code used to compute performance metrics).

7. Acknowledgements

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